Large shocks in U.S. macroeconomic time series: 1860-1988

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Abstract

In this paper we examine the large shocks due to major economic or financial events that affected U.S. macroeconomic time series on the period 1860–1988, using outlier methodology. We show that most of these shocks have a temporary effect, showing that the U.S. macroeconomic time series experienced only few large permanent shifts in the long term. Most of these large shocks can be explained by the Great Depression, World War II and recessions as well as by monetary policy for the interest rate data. We also find that some economic events seem to have the same effect or the same type of outliers on a number of macroeconomic series. Finally, we show that macroeconomic time series do not seem inconsistent with a stochastic trend once we adjusted the data of these shocks.

Keywords: Macroeconomic time series; large shocks; outliers.

JEL Classification: C22; N1.

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1 Introduction

Relatively infrequent but major economic events can have dramatic effects on the economy, especially for long-term economic series. This type of event includes, for example, the 1973 and 1979 oil crises, the major twentieth century wars, recessions, financial slumps, changes of political regimes, natural catastrophes, etc (Balke and Fomby, 1994; Darné and Diebolt, 2004). Furthermore, Blanchard and Simon (2001) argued that "*recessions are largely the result of infrequent large shocks - indeed, sufficiently large and identifiable that they often have names: the first and second oil shocks, the Volcker disinflation, and so on*". Therefore, it is important to analyze these infrequent large shocks. We thus examine the large shocks due to major economic or financial events that affected U.S. macroeconomic time series on the period 1860–1988, collected by Nelson and Plosser (1982), using outlier methodology (e.g., Box and Tiao, 1975; Tsay, 1988a; Chen and Liu, 1993a). This approach considers that these major shocks occur infrequently (low-frequency shocks) but the time of their arrival is random. We attempt to identify these shocks which can have a permanent or temporary effect, in the form of outliers, providing a certain amount of information about the nature and magnitude of the economic shocks in the U.S.

Outliers may have a significant impact on the results of standard methodology for time series analysis, therefore it is important to detect them, estimate their effects and undertake the appropriate corrective actions. For example, the impact of outliers on the identification of linear ARMA models has been studied by Peña (1990) and Deutsch et al. (1990) and on nonlinear models by van Dijk et al. (1999) and Battagila and Orfei (2005), and the effects on forecasts are addressed by Ledolter (1989) and Chen and Liu (1993b).

Moreover, some studies showed that the unit root tests can be biased by the structural breaks (e.g., Perron, 1989; Rappoport and Reichlin, 1989; Montañés and Reyes, 1998; Leybourne et al., 1998; Sen, 2008) and outliers (Franses and Haldrup, 1994; Lucas, 1995; Shin et al., 1996; Yin and Maddala, 1997), especially additive outliers which affect only a single observation at some points in time series and not its future values.[1] Since the influential paper of Nelson

[1] A number of tests has been then developed to take into account a structural change in which the date of the break is *a priori* unknown (e.g., Zivot and Andrews, 1992; Li, 1995; Perron, 1997; Sen, 2004; Montañés et al., 2005). Vogelsang (1999), Perron and Rodriguez (2003) and Haldrup and Sansó (2008) suggested procedures for detecting multiple additive

and Plosser (1982), much attention has been devoted to examining whether macroeconomic time series are trend or difference stationary. Indeed, if the series is trend stationary, and is thus characterized by stationary movements around a deterministic trend, a shock has temporary effect and the series returns to its steady trend after the shock. On the other hand, if the series is difference stationary (or has a unit root), and is therefore characterized by a random walk (possibly with a drift), a shock has persistent effect. As a result, the series does not return to its former path following a random disturbance, and the level of the series shifts permanently. Applying the Dickey-Fuller unit root tests on a wide variety of U.S. macroeconomic time series, Nelson and Plosser (1982) found that the null hypothesis of a unit root could be rejected for only one out of the fourteen macroeconomic time series in their data set, i.e. the unemployment rate. Their finding had a profound impact on the way economic series have been viewed and treated subsequently (Banerjee and Urga, 2005), especially if the series were indeed integrated, random shocks would have a permanent effect on the economy. However, several authors pointed out that the tests employed by Nelson and Plosser have a drawback with the presence of breaks and outliers.[2] Furthermore, they argued that the majority of shocks to the key economic variables of any economy would be transitory and that only few (rare) events would have any permanent effect. For these reasons, we re-analyze the presence of a unit root in the Nelson-Plosser data set by applying efficient unit root tests – developed by Elliott, Rothenberg and Stock (1996) and Ng and Perron (2001) – on the series corrected by previously detected outliers. This approach allows to distinguish between frequent small shocks due to period-by-period permanent innovations (as in the case of a stochastic trend) and infrequent large shocks due to significant economic and financial events. Our results point out the presence of a unit root for thirteen out of the fourteen series in the Nelson-Plosser data set, and therefore confirm the findings of Nelson and Plosser (1982), namely U.S. macroeconomic time series do not seem inconsistent with a stochastic trend.

The outline of the paper is as follows. In Section 2, the methodology for detecting outliers is described, and the detected outliers which can be associated to some major economic or financial events are discussed in Section 3. Section

outliers in nonstationary time series.

[2]See Appendix for selected studies on the estimated break dates in the Nelson-Plosser data set.

4 presents the unit root tests and interprets the results. Section 5 concludes.

2 Outlier Methodology

The search for outliers considers an unobserved components model in which there are two components: a regular component and an outlier component.[3] This outlier component reflects extraordinary, infrequently occurring events or shocks that have important effects on macroeconomic time series. The model is given by

$$z_t = y_t + f(t) \tag{1}$$

where

$$y_t = \frac{\theta(L)}{\alpha(L)\phi(L)} a_t \qquad\qquad a_t \sim N(0, \sigma_a^2) \tag{2}$$

y_t is an ARIMA(p, d, q) process and $f(t)$ contains exogenous disturbances or outliers. Following Chen and Liu (1993a), we will consider four types of outliers: additive outlier (AO), innovation outlier (IO), level shift (LS), and temporary change (TC). The models for different $f(t)$ are as follows

$$\begin{aligned} \text{AO:} \quad & f(t)_{AO} = \omega_{AO} I_t(\tau) \\ \text{LS:} \quad & f(t)_{LS} = [1/(1-L)]\omega_{LS} I_t(\tau) \\ \text{IO:} \quad & f(t)_{IO} = [\theta(L)/\alpha(L)\phi(L)]\omega_{IO} I_t(\tau) \\ \text{TC:} \quad & f(t)_{TC} = [1/(1-\delta L)]\omega_{TC} I_t(\tau) \end{aligned} \tag{3}$$

where ω_i, $i =$ AO, IO, LS, TC, denotes the magnitudes of the outlier, and $I_t(\tau)$ is an indicator function with the value of 1 at time $t = \tau$ and 0 otherwise, with τ the date of outlier occurring.

These outliers affect the observations differently: AO causes an immediate and one-shot effect on the observed series; LS produces an abrupt and permanent step change in the series (permanent shock); TC produces an initial effect, and this effect dies out gradually with time, where the parameter δ is designed to model the pace of the dynamic dampening effect ($0 < \delta < 1$); the effect of IO is more intricate than the effects of the others types of outliers[4]. IO will produce

[3] Another possibility to deal with outliers in the ARIMA framework is given by the structural time series models and available in the STAMP software (Koopman et al., 2006). See Metz (2010) for an application on Chile's per capita GDP.

[4] Indeed, except for the case of IO, the effects of outliers on the observed series are independent of the model.

a temporary effect for a stationary series whereas it will produce a permanent level shift for a nonstationary series (see Chen and Liu, 1993a).
It is considered that AOs and IOs are outliers which are related to an exogenous and endogenous changes in the series, respectively, and that TCs and LSs are more in the nature of structural changes. TCs represent ephemeral shifts in a series whereas LSs are more the reflection of permanent shocks. However, IOs will have a relatively persistent effect on the level of the series. Note that LSs and (nonstationary) IOs detected in level of the time series correspond to additive or innovative outliers in first-difference, i.e. in growth rates (Balke and Fomby, 1991; Maddala and Kim, 2000).

The methods are well-developed in the field of outlier detection based on intervention analysis as originally proposed by Box and Tiao (1975). This approach requires iterations between stages of outlier detection and estimation of an intervention model. Procedures considered by Chang et al. (1988) and Tsay (1988a) are quite effective in detecting the locations and estimating the effects of large isolated outliers. However, these procedures display some drawbacks: (i) the presence of outliers may result in an inappropriate model; (ii) even if the model is appropriately specified, outliers in a time series may still produce bias in parameter estimates and hence may affect the efficiency of outlier detection; and (iii) some outliers can not be identified due to a masking effect. To overcome these problems, Chen and Liu (1993a) proposed an iterative outlier detection and adjustment procedure to obtain joint estimates of model parameters and outlier effects. In their procedure the types and effects of outliers are obtained based on less contaminated estimates of model parameters, the outlier effects are estimated simultaneously using multiple regression, and the model parameters and the outlier effects (ω_i) are estimated jointly.[5] Here we use the Chen-Liu method modified by Gómez and Maravall (1997) and implemented in the computer program TRAMO (Time Series Regression with ARIMA Noise, Missing Observations, and Outliers) allowing the automatic iterative identification of all four types of outlier.[6] This procedure is described below.

[5]From a simulation study, Chen and Liu (1993a) showed that their procedure performs well in terms of detecting outliers and obtaining unbiased parameter estimates.

[6]Franses and Haldrup (1994), Tolvi (2001) and Darné and Diebolt (2004) also used this method to detect and correct outliers in macroeconomic series whereas Balke and Fomby (1991, 1994) and Bradley and Jansen (1995) applied that of Tsay (1988a).

An ARIMA model is fitted to y_t in (2) and the residuals are obtained

$$\hat{a}_t = \pi(B) z_t \tag{4}$$

where $\pi(B) = \alpha(B)\phi(B)/\theta(B) = 1 - \pi_1 B - \pi_2 B^2 - \ldots$.

For the four types of outliers in (1), the equation (4) becomes

$$\begin{aligned}
\text{AO:} \quad & \hat{a}_t = a_t + \omega_{AO}\pi(B) I_t(\tau) \\
\text{IO:} \quad & \hat{a}_t = a_t + \omega_{IO} I_t(\tau) \\
\text{LS:} \quad & \hat{a}_t = a_t + \omega_{LS}[\pi(B)/(1-B)] I_t(\tau) \\
\text{TC:} \quad & \hat{a}_t = a_t + \omega_{TC}[\pi(B)/(1-\delta B)] I_t(\tau)
\end{aligned}$$

These expressions can be viewed as a regression model for $\hat{a}_t$, i.e.,

$$\hat{a}_t = \omega_i x_{i,t} + a_t \qquad i = \text{AO, IO, LS, TC},$$

with $x_{i,t} = 0$ for all i and $t < \tau$, $x_{i,t} = 1$ for all i and $t = \tau$, and for $t > \tau$ and $k \geq 1$, $x_{AO,t+k} = -\pi_k$ (AO), $x_{IO,t+k} = 0$ (IO), $x_{LS,t+k} = 1 - \sum_{j=1}^{k} \pi_j$ (LS) and $x_{TC,t+k} = \delta^k - \sum_{j=1}^{k-1} \delta^{k-j}\pi_j - \pi_k$ (TC).

The detection of the outliers is based on likelihood ratio [LR] statistics, given by

$$\begin{aligned}
\text{AO:} \quad & \hat{\tau}_{AO}(\tau) = [\hat{\omega}_{AO}(\tau)/\hat{\sigma}_a] / \Big(\sum_{t=\tau}^{n} x^2_{AO,t}\Big)^{1/2} \\
\text{IO:} \quad & \hat{\tau}_{IO}(\tau) = \hat{\omega}_{IO}(\tau)/\hat{\sigma}_a \\
\text{LS:} \quad & \hat{\tau}_{LS}(\tau) = [\hat{\omega}_{LS}(\tau)/\hat{\sigma}_a] / \Big(\sum_{t=\tau}^{n} x^2_{LS,t}\Big)^{1/2} \\
\text{TC:} \quad & \hat{\tau}_{TC}(\tau) = [\hat{\omega}_{TC}(\tau)/\hat{\sigma}_a] / \Big(\sum_{t=\tau}^{n} x^2_{TC,t}\Big)^{1/2} \\
\text{with} \quad & \hat{\omega}_i(\tau) = \sum_{t=\tau}^{n} \hat{a}_t x_{i,t} \Big/ \sum_{t=\tau}^{n} x^2_{i,t} \qquad \text{for } i = \text{AO, LS, TC}, \\
\text{and} \quad & \hat{\omega}_{IO}(\tau) = \hat{a}_\tau
\end{aligned}$$

where $\hat{\omega}_i(\tau)$ ($i =$ AO, IO, LS, TC) denotes the estimation of the outlier impact at time $t = \tau$, and $\hat{\sigma}_a$ is an estimate of the variance of the residual process (Chang et al., 1988).

Outliers are identified through running a sequential detection procedure, consisting of an outer and an inner iterations. In the outer iteration, assuming that there are no outliers, an initial ARIMA(p, d, q) model is estimated and the residuals are obtained ($\hat{a}_t$). The results from the outer iteration are then used in the inner iteration to identify outliers. The LR test statistics for the four types of outliers are calculated for each observations. The largest absolute value of these test statistics

$$\hat{\tau}_{max} = max|\hat{\tau}_i(\tau)| \qquad\qquad i = \text{AO, IO, LS, TC and } \tau = 1, \ldots, T$$

is compared to a critical value, and if the test statistic is larger, an outlier is found at time $t = \tau_1$ and its type is selected (i^*). In TRAMO the critical value is determined by the number of observations in the series based on simulation experiments. When an outlier is detected, the effect of the outlier is removed from the data as follows: the observation z_t is adjusted at time $t = \tau_1$ to obtain the corrected y_t via (1) using the estimated magnitude $\hat{\omega}_{i^*}$ and the appropriate structure of outlier $f(t)_{i^*}$ as in (3), i.e.

$$y_t = z_t - f(t)_{i^*}$$

Then, we compare the second largest absolute value of the LR statistics for the four types of outliers to the critical value, i.e. $\hat{\tau}_{max} = max|\hat{\tau}_i(\tau)|$ with $\tau \neq \tau_1$, and so on. This process is repeated until no more outliers can be found. Next, return to the outer iteration in which another ARIMA(p, d, q) model is re-estimated from the outlier-corrected data, and start the inner iteration again. This procedure is repeated until no outlier is found. Finally, a multiple regression is performed on the various outliers detected to identify (possible) spurious outliers.[7]

To decide on a specific basic ARIMA model, we evaluated different alternatives: ARIMA(0,1,0), ARIMA(0,1,1), ARIMA (1,1,0), ARIMA(1,1,1), ARIMA(0,1,2) and ARIMA(2,1,0). The chosen ARIMA model is based on specification tests and information criteria.

Note that estimating the initial ARIMA(p, d, q) model can lead to misidentify level shifts as innovational outliers or not detect them. To better determine whether the outliers can be considered as permanent or not, an outlier search will be conducted using the series in levels, i.e. from an ARIMA$(p, 0, q)$ (Balke and Fomby, 1991; Balke, 1993).

[7] See Tolvi (2001) for detailed discussion on the outlier detection procedure.

3 Infrequent Large Shocks and Nelson-Plosser data set

We study the 14 annual U.S. macroeconomic data set used by Nelson and Plosser (1982): Real GNP, nominal GNP, real per capita GNP industrial production, employment, unemployment, GNP deflator, consumer price, nominal wages, real wages, money stock, velocity, interest rate, and stock price. The data consists of annual observations which begins between 1860 and 1909. In this paper we consider an extension of the Nelson-Plosser data set to include the observations up to 1988. This extension was compiled by Schotman and van Dijk (1991). The logarithmic transformation is applied on the data, except for the interest rate.

3.1 Descriptive Statistics

Tables 1 and 2 display the ARIMA specifications for all the variables. As suggested by Andreou and Spanos (2003), we also report some descriptive statistics from ARIMA models to assess statistical adequacy[8]: normality, non-autocorrelation, homoskedasticity and linearity (Tables 3 and 4). The normality coefficients used are skewness, kurtosis and Jarque-Bera. We employ the Box-Pierce [BP] test for the non-autocorrelation, the Lagrange Multiplier [LM] test for the homoskedasticity (Engle, 1982) and the BDS test statistic for the non-linearity (Brock, Dechert and Scheinkman, 1987).

Most of the original series indicate significant skewness and excess kurtosis implying that the assumption of gaussian errors is not appropriate. As shown by Balke and Fomby (1994) and Carnero et al. (2001), outliers may cause significant skewness and excess kurtosis in macroeconomic time series. Indeed, these measures of non-normality decrease, sometimes quite dramatically, after correcting outliers. Evidence of excess skewness and excess kurtosis disappears for all the series, except for the industrial production, the GNP deflator and the nominal wages.

The BP statistics are not significant for all (outlier unadjusted and adjusted) series. This means that there is no serial linear correlation, except in the stock

[8] Andreou and Spanos (2003) showed that several estimated models by Nelson and Plosser (1982) could be misspecified, thus potentially biasing the performance of the unit root tests. Based on estimated models which are statistically adequate, they obtained different conclusions on the unit root hypothesis.

price which displays a BP test significant when the data are corrected of outliers. This autocorrelation can be due to the presence of heteroscedasticity. In this context, we apply the Box-Pierce test corrected of conditional heteroscedasticity. This statistic appears insignificant, implying that there is no serial linear correlation in the stock price.

The data does not seem contain conditional heteroscedasticity since the LM tests are not significant for most of series. Moreover, the interest rate, the stock price, the nominal GNP and the industrial production display a significant LM test when the data are not corrected of outliers. Nevertheless, when these series are cleaned of outliers, the test becomes insignificant. This result confirms that of Carnero et al. (2001) and van Dijk et al. (2002) who showed that if outliers are neglected, the LM test rejects the null hypothesis of conditional homoscedasticity too often when it is true. The exception is the velocity which seems to present conditional heteroscedasticity even if the data are corrected of outliers.

Finally, to test for general non-linearity we apply the most widely used test: the BDS test. From Tables 3 and 4, we observe that all the uncorrected data, except the real wages and the stock prices, display non-linearity. However, the BDS test becomes insignificant when the outliers are removed for most of them. This result is consistent with that of Tsay (1988b), Petruccelli (1990), Balke and Fomby (1994), suggesting that the presence of outliers in a linear time series can cause the false detection of non-linearity. For example, Balke and Fomby (1994) showed that after fitting the outlier model and controlling for the effects of the outliers, the evidence of non-linearity in fifteen post-World War II macroeconomic time series is substantially weaker. The nominal GNP and wages, the industrial production and the velocity have strong evidence of non-linearity even after removing the effect of outliers.[9]

3.2 Infrequent Large Shocks

In Tables 5-8, all detected outliers are given by series, with their type, timing and t-statistics. In addition, we also try to associate the date of each outlier to a specific event that occurred near that date.

As expected, outliers are detected in all the series, giving strong proof of infrequent large shocks. Most of the shocks have a temporary effect but only

[9]The non-linearity displays by the velocity can be explained by the presence of conditional heteroscedasticity.

seven out of fourteen series experience one permanent shock (i.e. 8% of the detected outliers), showing that the U.S. macroeconomic time series experienced only few large permanent shifts in the long term.[10] As suggested by Balke and Fomby (1994) and Darné and Diebolt (2004), it can also be noted that most of the series experienced an infrequent large shock due to the Great Depression, World War II and recessions. Below we examine further the detected outliers that are linked with identifiable economic events for all the series. Since there is a clustering of outliers across series, i.e. an event can cause infrequent large shocks in different series, we describe chronologically the economic events which could affect the series.

The expansion of 1862-1864 during the U.S. civil war can explain the positive shocks experienced by the consumer price. The shocks in 1893 and 1894 can be caused by the recession of 1893-1894. In 1893, some railroad companies were placed in receivership, heralding the panic of 1893. Indeed, the stock prices declined sharply, involving hundreds of business failures and bank closings.[11]

The negative shock in 1906 can be explained by the expansion of 1905-1906 which was characterized by the growth of the productive system, in particular the construction of railroads. The negative shock detected in 1908 can be due to the short, but extremely severe, recession of 1907-1908. Indeed, in 1906 the Bank of England decided to discriminate against American finance bills and, along with other European central banks, to raise interest rates. These actions attracted gold import and sharply reduced the flow of gold to the U.S. and thus involved the financial and banking panic of 1907.[12]

The shocks in 1916, 1917 and 1918 can be caused by World War I and the expansion of 1915-1918. This period was characterized by high inflation which reflected massive gold imports from the European belligerents buying war materiel as well as inflationary finance once the U.S. entered the war in 1917 (Bordo and Haubrich, 2004). The recession of 1920-1921 can explain the negative shocks identified in 1920 and 1921. This recession can be caused by

[10] Note that using the ARIMA(0,1,0) model to improve the power of level shift detection, no level shift is misidentified as innovative outliers.

[11] Carlson (2005) suggested that real economic shocks were important determinants of the nationwide scope of the panic of 1893, however at the local level, liquidity concerns are found to be a more important trigger of bank panics.

[12] Odell and Weidenmier (2004) analyzed links between the 1906 San Francisco earthquake and the panic of 1907. Note that this panic led to an important change in American financial architecture: the creation of the Federal Reserve System that was established in 1913.

the inflationary financing during World War I which involved the U.S. to lead a deflationary policy. The shocks in 1923 can be due to the rapid recovery which followed the recession.

The shock in 1928 can be attributed to the tight monetary policy led by the Fed to contain developing stock market bubble, which was perceived as a threat to the continued progress and stability of the economy (Orphanides, 2003). This tight policy led into the stock market crash of October 1929 and the beginning of the Great Depression. All the series, except the consumer price, the real wages and the velocity, experienced large shocks detected in 1930, 1931 and 1932 which can be caused by the Great Depression during the 1930s in U.S. following the stock market crash in 1929. Indeed, the period 1929-1933 consisted of a decline in economic activity, characterized by repeated failures of the new Federal Reserve System to offset the monetary collapse triggered by several waves of banking panics (Friedman and Schwartz, 1963). The recession of 1937-1938 can explain the negative shocks in 1938. This recession can be explained by a decline of economic activity and the reduction of the finance public deficit. Friedman and Schwartz (1963) attributed this downturn to a monetary contraction resulting from an increase in reserve requirements.

World War II had a strong impact on the period 1942-44 due to the large rise in military spending as soon as the U.S. had entered in war. During World War II, government expenditures were financed primarily by issuing debt. The U.S. economy was strongly affected in 1946 by the end of World War II due to the readjustments in the economy after the wartime economy.

The post-WWII infrequent large shocks are only experienced by the interest rate series, except the employment and the real per capita GDP in 1954. The negative shocks in 1954 can be explained by the short recession of 1953-1954 which was due to the readjustments in the expenditures after the end of the Korean war.

The shock in 1957 can be attributed to the fear of inflation which led the Fed to tight monetary policy.[13] The less restrictive monetary policy led by the Fed, especially to avoid the aggravation of payments balance deficit, can explain the shock in 1961. The shocks in 1968 and 1970 can be caused by U.S. expansionary monetary and fiscal policies to finance social programs and the Vietnam War from 1968 which implied the recession of 1970. The shocks in 1980 and 1981 can

[13]See Friedman and Schwartz (1963), Romer and Romer (1989) and Taylor (1998), *inter alia*, for a discussion on U.S. monetary history and policy.

be due to the Volcker aggressive disinflationary policy to stabilize the inflation and the economy which was accompanied by a severe recession. The shock in 1984 can be explained by the preemptive interest rate policy actions led by the Fed in 1983-84 to contain the inflation scare (Goodfriend, 2005) or can be owing to the substantial federal budget deficit that began in 1981 (Campbell and Clarida, 1987). Finally, the shock in 1986 can be owing to an oil price decline as well as the importance of the strong dollar (Poole, 1988).

Table 9 organizes the same information in a different way, displaying the events associated with the type of outliers in chronological order and listing the series that have outliers with this event. Table 9 shows some patterns that appear to exist among the outliers and that are linked with economic events. First, many of the identified outliers seem to be associated with business cycles, particularly recessions (62% of the detected outliers). Second, some economic events seem to have the same effect on a number of macroeconomic series, for example, the Great Depression and WWI had a temporary effect for twelve and nine of the fourteen macroeconomic time series, respectively, especially an innovative outlier for nine and five series, respectively. Third, some events seem to be associated with one type of outliers for the detected outliers, for example, the recession of 1937-1938 is associated with a temporary change whereas the end of WWI is rather associated with an innovative outlier.

We compare the estimated break dates obtained in some previous studies on Nelson-Plosser data set with our detected outliers (see Tables 11-12 in Appendix). The selected studies are the tests for detecting breaks proposed by Volgelsang (1997) (from level [V1] and first-difference [V2] statistics) and Hsu and Kuan (2001) [HK] as well as the unit root tests with one structural break suggested by Zivot and Andrews (1992) [ZA] and Perron (1997) (from two different statistics, [P1] and [P2]) and with two structural breaks proposed by Lumsdaine and Papell (1997) [LP], Lee and Strazicich (2003) [LS] and Papell and Prodan (2007) [PP]. Note that the estimated break dates from these studies are sometimes very different.
Most of the estimated break dates are close to the detected outliers with the higher t-statistics for all the series except for the stock price[14]. If T_B is the

[14] The outliers with the higher t-statistics for the interest rate are not located by the various tests as they investigated the Nelson-Plosser data set until 1970.

location of outliers, the corresponding estimated breaks are often located at $T_B \pm 1$ or ± 2. This result confirms that obtained by Lee and Strazicich (2001) who argued that the endogenous break unit root tests tend to incorrectly estimate the structural break.

Much breaks are estimated in the beginning of the 1920s and the 1930s as well as the end of the 1930s by the various tests. The shocks identified in 1920 and 1921 are generally located in 1919 and 1920 for the real (LS) and nominal GNP (LP, LS), the GNP deflator (P2, V1, LP), the consumer prices (P2), the nominal wages (P2, V2) and the money stock (V2). LS found these breaks for most of the series whereas ZA, P1, HK and PP did not identify shocks due to the recession of 1920-1921. The outliers identified in the beginning of the 1930s are estimated in 1928 or 1929 for the GNP series as well as for the industrial production, the employment, the nominal wages and the money stock by the various tests, and in 1930 for some series by HK. The recession in 1938 is estimated in 1937, 1938, 1939 and 1940 for the real (p.c.) GNP and the real wages according to the different tests.

Some estimated breaks correspond to some detected outliers but only for a few of tests. For the GNP deflator, the shock in 1917 is located in 1916 by LP and the shock in 1946 is estimated in 1945 by PP. The shock in 1917 for the consumer prices is identified in 1916 by LS. For the wages series, the shock in 1908 is located in 1908 (nominal) and 1909 (real) by PP, whereas the shocks in 1916 and in 1941 are estimated in 1914 by LP and in 1942 by LS, respectively. For the employment, the shock in 1908 is located in 1906 by V2 and in 1908 by PP, whereas the shock in 1954 is estimated in 1955 by LP and that of 1946 in 1945 by LS. The shock in 1917 for the money stock is estimated in 1915 by PP. For the interest rate, the shock in 1957 is located in 1957 and in 1958 by LP and LS, respectively; the shock in 1961 is estimated in 1962 and in 1963 by V1 and P1, respectively; and the shock in 1968 is identified in 1967 by V2. The shock in 1881 for the velocity is estimated in 1880 by P2, in 1883 by LP and in 1884 by PP.

Finally, the locations of the estimated breaks for the consumer prices, the velocity and the stock prices are very different than those of the detected outliers.

4 Application of Unit Root Tests

Since the outliers can seriously affect the unit root tests (e.g., Franses and Haldrup, 1994; Lucas, 1995), we apply two efficient unit root tests proposed by Elliott, Rothenberg and Stock (1996) [ERS] and Ng and Perron (2001) [NP] on the outlier-adjusted Nelson-Plosser data set[15].

ERS (1996) developed a unit root test based on a quasi-difference detrending of the series in order to increase power of Dickey-Fuller tests. They suggested the Dickey-Fuller generalized least squares (DF-GLS) test using the following regression

$$\Delta y_t^d = \beta_0 y_{t-1}^d + \sum_{j=1}^{k} \beta_j \Delta y_{t-j}^d + \varepsilon_t$$

where y_t^d is the locally detrended series y_t. The DF-GLS t-test is performed by testing the null hypothesis $\beta_0 = 0$ against the alternative $\beta_0 < 0$. The local detrending series is defined by

$$y_t^d = y_t - \hat{\psi}' z_t$$

where z_t equals to 1 for the constant mean case, and $(1, t)$ for the linear trend case, and $\hat{\psi}$ is the GLS estimator obtained by regressing $\bar{y}$ on $\bar{z}$ where

$$\begin{aligned} \bar{y} &= (y_1, (1 - \bar{\alpha}B)y_2, \ldots, (1 - \bar{\alpha}B)y_T)' \\ \bar{z} &= (z_1, (1 - \bar{\alpha}B)z_2, \ldots, (1 - \bar{\alpha}B)z_T)' \end{aligned}$$

and $\bar{\alpha} = 1 + \bar{c}/T$. ERS advise $\bar{c} = -7$ for the constant mean case and $\bar{c} = -13.5$ for the linear trend case.

Ng and Perron (2001) proposed modifications of the Phillips-Perron test, which is a non-parametric approach to correct residual autocorrelation by modifying the Dickey-Fuller test statistics, first, to correct the size distortions (as suggested by Perron and Ng, 1996), second, to improve the power (as suggested by ERS, 1996). The NP test is based on the following regression

$$\Delta \tilde{y}_t = (\hat{\delta} - 1)\tilde{y}_{t-1} + \sum_{j=1}^{k} \hat{\phi}_j \Delta \tilde{y}_{t-j} + \hat{\varepsilon}_t$$

[15] Darné and Diebolt (2004) studied the sensitivity of the unit root tests to the two-steps tests (correcting outliers and testing unit roots on outlier-adjusted data) from simulation experiments. They showed that this procedure does not affect the presence of unit roots in time series. Osborn, Heravi and Birchenhall (1999) also used this procedure for testing seasonal unit roots.

where $\tilde{y}_t$ is the locally detrended series y_t. Under the unit root null hypothesis, $\hat{\delta} = 1$; thus the NP test statistics, called M-GLS tests, are

$$\begin{aligned} MZ_t &= \left(T^{-1}\tilde{y}_T^2 - s^2\right)\left(4s^2T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2\right)^{-1/2} \\ MZ_a &= \left(T^{-1}\tilde{y}_T^2 - s^2\right)\left(2T^{-2}\sum_{t=1}^{T}\tilde{y}_{t-1}^2\right)^{-1} \end{aligned}$$

where s is the autoregressive spectral density estimator of the long-term variance.

Furthermore, Ng and Perron (2001) showed that the popular Akaike and Schwarz information criteria are not sufficiently flexible for unit root tests, mainly when there are negative moving-average errors, to select the appropriate number of lags k in the regression.[16] They therefore suggested the use of Modified Information Criteria (MIC) that gives better results when an appropriate value for lags k is chosen for the DF-GLS and M-GLS tests.

The results of unit root test are displayed in Table 10. The lag order k in the regression is selected by using the MIC. The efficient unit root tests for all the variables do not reject the unit root null hypothesis at the 5% level[17], except for the unemployment. Contrary to the recent studies on the Nelson-Plosser data set, this result confirms the findings of Nelson and Plosser (1982), namely 13 of the 14 macroeconomic time series of interest have a stochastic trend.[18] Therefore, it seems that the fluctuations of U.S. macroeconomic time series can be explained by both low-frequency due to major economic events, especially temporary shocks, and high-frequency shocks due to a stochastic trend. These

[16] Ng and Perron (2001) argued that the Akaike and Schwarz information criteria tend to select values of k that are generally too small for unit root tests to have good sizes.

[17] Since the nominal GNP, the industrial production, the nominal wages and the velocity present some non-linearity we also used the nonlinear unit root test proposed by Kapetanios et al. (2003). The unit root test developed by Seo (1999) is also applied on the velocity in which conditional heteroscedasticity has been detected. The results obtained from these unit root tests are identical with those from the efficient unit root tests.

[18] From unit root tests with two structural breaks, at the 5% significance level, the null of unit root is rejected for six series (real (p.c.) and nominal GNP, industrial production, employment and unemployment) with the Lumsdaine-Papell test; for four series (industrial production, unemployment, real wage and money stock) with the Lee-Strazicich test; and for three series (real (p.c.) GNP and employment) with the Papell-Prodan test when considering model A in all series and model C for the real wages and the stock prices. Note that Papell and Prodan (2007) did not study the unemployment.

differences may result from (i) the presence of non-linearity, (ii) the presence of outliers, (iii) the imposing of a maximum of one or two breaks in the series, and (iv) the choice of model studied according to the type of break.

5 Conclusion

This paper examined the presence of large, but infrequent shocks due to major economic or financial events on U.S. macroeconomic time series, using outlier methodology. We showed that most of the shocks have a temporary effect, showing that the U.S. macroeconomic time series experienced only few large permanent shifts in the long term. Most of these large shocks can be explained by the Great Depression, World War II and recessions as well as by monetary policy for the interest rate data. We also found that some economic events seem to have the same effect or the same type of outliers on a number of macroeconomic series.

We showed that these large shocks in the form of outliers affected the normality coefficients and non-linearity, and mostly, the evidence for non-normality and non-linearity is reduced after correcting for outliers. Therefore, taking into account these events can improve modeling of macroeconomic time series. Furthermore, once we adjusted the data of these outliers, our results pointed out the presence of a unit root for 13 of the 14 Nelson-Plosser macroeconomic time series. Therefore, as suggested by Nelson and Plosser (1982), macroeconomic time series do not seem inconsistent with a stochastic trend, suggesting that the fluctuations of U.S. macroeconomic time series can be explained by both low-frequency (due to major economic events) and high-frequency shocks (due to a stochastic trend).

Future research should investigate the presence of a unit root by applying a Dickey-Fuller test corrected for detected outliers based on intervention models or robust unit root tests.

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Table 1: Descriptive Statistics from ARIMA Models.

Series	Sample	T	ARIMA Model	Type	Skew	Kur	JB	BP(10)
Real GNP	1909-1988	80	(0,1,1)	o	-0.17	4.04	3.87	11.13
				c	0.18	2.86	0.47	6.90
Nominal GNP	1909-1988	80	(0,1,1)	o	-0.99*	6.96*	63.72*	15.45
				c	0.28	3.57	2.07	11.26
Real per capita GNP	1909-1988	80	(0,1,1)	o	-0.24	3.87	3.15	12.00
				c	0.04	2.42	1.13	15.40
Industrial production	1860-1988	129	(2,1,0)	o	-0.76*	3.87*	16.39*	21.99*
				c	-0.46*	3.67	6.80*	2.91
Employment	1890-1988	99	(1,1,1)	o	-0.49*	3.97*	7.69*	8.72
				c	-0.02	3.89	3.20	5.99
Unemployment	1890-1988	99	(2,0,0)	o	-0.04	4.74*	12.44*	7.00
				c	0.35	3.14	2.06	6.13
GNP deflator	1889-1988	100	(0,1,1)	o	-1.33*	11.87*	349.85*	4.45
				c	0.17	4.45*	8.95*	8.74
Consumer Price	1860-1988	129	(1,1,0)	o	-1.32*	9.82*	282.88*	4.27
				c	-0.19	3.19	0.95	7.05

o: original series, c: corrected-outliers series. * Significant at the 5% level. The BP test follow a χ^2 distribution with $10 - p - q$ degrees of freedom under the null hypothesis of no serial linear correlation (with p and q the AR and MA orders, respectively).

Table 2: Descriptive Statistics from ARIMA Models (continue).

Series	Sample	T	ARIMA Model	Type	Skew	Kur	JB	BP(10)
Nominal wages	1900-1988	89	(0,1,2)	o	-0.46	5.75*	30.34*	8.61
				c	0.04	4.17*	4.96	9.98
Real wages	1900-1988	89	(1,1,0)	o	0.05	3.18	0.15	4.37
				c	-0.01	3.50	0.90	7.45
Money stock	1889-1988	100	(0,1,1)	o	-0.35	5.14*	20.70*	3.71
				c	0.23	2.82	0.99	5.13
Velocity	1869-1988	120	(0,1,1)	o	-0.47*	3.51	5.62*	11.39
				c	-0.36	3.12	2.70	8.61
Interest rate	1900-1988	89	(2,1,0)	o	-0.41	6.40*	43.29*	7.17
				c	0.31	2.32	3.01	8.14
Stock price	1871-1988	118	(0,1,1)	o	-0.45*	4.29*	12.03*	11.35
				c	-0.04	2.46	1.43	17.28*

o: original series, c: corrected-outliers series. * Significant at the 5% level. The BP test follow a χ^2 distribution with $10-p-q$ degrees of freedom under the null hypothesis of no serial linear correlation (with p and q the AR and MA orders, respectively).

Table 3: Tests for ARCH and Non-linearity.

Series	Type	LM(1)	LM(4)	BDS(0.5,2)	BDS(0.5,3)	BDS(0.5,4)	BDS(1,2)	BDS(1,3)	BDS(1,4)
Real GNP	o	0.07	6.14	1.79	4.10*	4.70*	2.30*	4.49*	5.17*
	c	1.10^{-5}	2.82*	1.94	1.22	2.17*	0.40	0.61	0.25
Nominal GNP	o	8.77*	12.78*	5.27*	7.73*	10.83*	3.32*	4.40*	5.73*
	c	0.48	6.60	3.04*	5.01*	6.20*	3.02*	4.14*	5.35*
Real per capita GNP	o	0.55	8.31	2.64*	4.56*	5.07*	2.35*	4.57*	5.47*
	c	0.25	3.02*	2.06*	2.10*	0.01	1.53	1.01	0.62
Industrial production	o	13.79*	16.01*	4.65*	5.60*	5.63*	4.37*	5.10*	5.47*
	c	0.86	2.66	2.33*	3.37*	3.59*	0.73	1.20	1.42
Employment	o	2.94	7.63	2.92*	4.95*	5.87*	3.23*	4.26*	4.91*
	c	0.51	1.39	0.29	1.32	1.82	0.38	0.40	0.58
Unemployment	o	0.10	2.02	3.39*	4.31*	4.95*	3.69*	4.63*	5.13*
	c	2.09	3.41	-1.01	-1.49	-1.39	-2.43	-2.16	-1.83
GNP deflator	o	2.70	8.54	3.66*	6.47*	9.42*	3.68*	4.75*	5.56*
	c	0.57	0.87	1.57	1.48	3.17*	0.52	1.61	1.70

o: original series, c: corrected-outliers series. * Significant at the 5% level. We examine the BDS statistic for embedding dimensions m=2,3, and 4 and $epsilon$=0.5 and 1 as suggested by Brock, Dechert and Scheinkman (1996). The BDS test follows a standard normal distribution under the null hypothesis.

Table 4: Tests for ARCH and Non-linearity (continue).

Series	Type	LM(1)	LM(4)	BDS(0.5,2)	BDS(0.5,3)	BDS(0.5,4)	BDS(1,2)	BDS(1,3)	BDS(1,4)
Consumer price	o	13.27*	6.63	4.64*	4.86*	6.08*	5.02*	4.67*	4.28*
	c	0.06	3.90	1.59	3.02*	5.80*	0.10	0.82	1.50
Nominal wages	o	0.71	6.28	3.63*	5.08*	5.72*	3.09*	4.72*	5.65*
	c	1.46	2.29	4.16*	4.14*	3.48*	2.98*	3.60*	3.89*
Real wages	o	0.12	4.56	-0.57	-0.22	-0.67	0.65	2.26*	2.58*
	c	0.02	1.86	-0.14	-0.30	-1.06	-1.06	-0.32	-0.16
Money stock	o	0.10	3.21	3.63*	4.49*	5.03*	2.49*	3.02*	4.19*
	c	1.69	5.50	1.22	0.41	0.64	1.23	0.62	0.65
Velocity	o	3.56	11.13*	1.42	3.69*	5.51*	2.15*	4.53*	5.64*
	c	10.46*	14.42*	4.02*	5.62*	7.30*	4.45*	6.04*	6.96*
Interest rate	o	15.59*	19.74*	4.08*	5.95*	7.10*	4.47*	5.51*	5.62*
	c	4.02	5.50	0.80	0.48	0.74	2.32*	1.07	1.57
Stock price	o	21.57*	23.67*	0.54	1.52	0.63	0.82	1.68	1.58
	c	1.64	5.16	-2.73	-3.21	-5.63	-1.66	-0.49	-0.80

o: original series, c: corrected-outliers series. * Significant at the 5% level. We examine the BDS statistic for embedding dimensions m=2,3, and 4 and $epsilon$=0.5 and 1 as suggested by Brock, Dechert and Scheinkman (1996). The BDS test follows a standard normal distribution under the null hypothesis.

Table 5: Outliers detection.

Series	Date	Type	t-stat	Events
Real GNP	1918	TC	4.32	World War I, expansion
	1921	AO	-5.39	Recession
	1930	IO	-4.50	Great Depression
	1932	IO	-5.08	Great Depression
	1938	TC	-3.79	Recession
	1946	IO	-4.05	End of World War II
Nominal GNP	1921	LS	-6.83	Recession
	1930	IO	-3.64	Great Depression
	1931	IO	-4.72	Great Depression
Real per capita GNP	1918	TC	5.67	World War I, expansion
	1921	AO	-6.03	Recession
	1930	IO	-4.82	Great Depression
	1932	IO	-5.49	Great Depression
	1938	TC	-4.34	Recession
	1946	IO	-4.10	End of World War II
	1954	AO	-3.71	Recession
Industrial production	1908	TC	-3.72	Recession
	1921	AO	-5.55	Recession
	1930	IO	-3.61	Great Depression
	1931	IO	-3.36	Great Depression
	1932	TC	-6.78	Great Depression
	1938	TC	-6.03	Recession
	1946	IO	-3.67	End of World War II

Table 6: Outliers detection (continue).

Series	Date	Type	t-stat	Events
Employment	1893	IO	-4.85	Recession
	1894	AO	-3.79	Recession
	1908	AO	-3.55	Recession
	1921	TC	-5.10	Recession
	1930	IO	-3.63	Great Depression
	1931	IO	-3.23	Great Depression
	1932	IO	-4.86	Great Depression
	1938	TC	-5.35	Recession
	1946	IO	-5.18	End of World War II
	1954	LS	-3.06	Recession
Unemployment	1893	TC	6.04	Recession
	1894	TC	3.30	Recession
	1906	IO	-4.01	Expansion
	1908	AO	3.94	Recession
	1918	IO	-5.11	World War I, expansion
	1920	IO	3.63	Recession
	1921	AO	3.05	Recession
	1923	AO	-5.18	Expansion
	1930	IO	3.99	Great Depression
	1931	TC	3.30	Great Depression
	1932	LS	6.36	Great Depression
	1942	LS	-5.41	World War II
	1943	IO	-4.32	World War II
	1944	IO	-3.11	World War II

Table 7: Outliers detection (continue).

Series	Date	Type	t-stat	Events
GNP deflator	1893	AO	4.74	Recession
	1916	IO	3.27	World War I, expansion
	1917	IO	4.22	World War I, expansion
	1920	AO	12.32	Recession
	1931	IO	-3.28	Great Depression
	1946	IO	3.01	End of World War II
Consumer price	1862	IO	3.28	Civil war, expansion
	1863	LS	4.89	Civil war, expansion
	1864	TC	8.77	Civil war, expansion
	1917	IO	3.36	World War I, expansion
	1921	IO	-7.36	Recession
Nominal wages	1908	TC	-7.13	Recession
	1916	IO	4.99	World War I, expansion
	1918	IO	4.81	World War I, expansion
	1921	IO	-7.50	Recession
	1923	TC	4.45	Expansion
	1932	IO	-5.06	Great Depression
	1938	TC	-5.52	Recession
	1941	IO	3.09	World War II
Real wages	1908	AO	-3.70	Recession
	1915	AO	-3.26	Recession
	1938	TC	-3.29	Recession
	1946	IO	-3.03	End of World War II

Table 8: Outliers detection (continue).

Series	Date	Type	t-stat	Events
Money stock	1893	IO	-4.27	Recession
	1908	AO	-4.45	Recession
	1917	IO	3.24	World War I, expansion
	1921	IO	-4.22	Recession
	1931	LS	-4.07	Great Depression
	1932	IO	-7.01	Great Depression
	1943	IO	4.84	World War II
	1945	TC	3.41	World War II
Velocity	1881	LS	-3.34	-
	1918	TC	3.21	World War I, expansion
Interest rate	1918	TC	6.04	World War I, expansion
	1928	AO	-3.72	Tight monetary policy
	1932	TC	8.67	Great Depression
	1957	AO	5.83	Tight monetary policy, recession
	1961	AO	-5.81	Less restrictive monetary policy
	1968	IO	5.42	Expansionary monetary and fiscal policies
	1970	AO	15.32	Expansionary monetary and fiscal policies
	1980	IO	9.93	Volcker disinflation, recession
	1981	TC	7.29	Volcker disinflation, recession
	1984	AO	19.98	Inflation scare
	1986	LS	-21.36	Fall in oil prices
Stock price	1932	TC	-5.19	Great Depression

Table 9: Chronology of events and type of outliers.

Events	Type	Series
Civil war, expansion	IO, LS	Consumer price
Recession (1893-1894)	IO	Employment, Money stock
	AO	Employment, GNP deflator
	TC	Unemployment
Expansion (1905-1906)	IO	Unemployment
Recession (1907-1908)	TC	Industrial production, Nominal wages
	AO	Employment, Unemployment, Real wages, Money stock
World War I, expansion	TC	Real (p.c.) GNP, Velocity, Interest rate
	IO	Unemployment, GNP deflator, Consumer price Nominal wages, Money stock
Recession (1920-1921)	AO	Real (p.c.) GNP, Industrial production, Unemployment
	IO	Consumer price, Nominal wages, Money stock, GNP deflator
	LS	Nominal GNP
Expansion (1923)	AO	Unemployment
	TC	Nominal wages
Tight monetary policy (1928)	AO	Interest rate
Great Depression	IO	Real (p.c.) GNP, Nominal GNP, Industrial production, Employment, Unemployment, GNP deflator Nominal wages, Money stock
	TC	Interest rate, Stock price
	LS	Unemployment, Money stock
Recession (1937-1938)	TC	Real (p.c.) GNP, Industrial production, Employment, Nominal wages, Real wages
World War II	LS	Unemployment
	IO	Unemployment, Nominal wages, Money stock
End of World War II	IO	Real (p.c.) GNP, Industrial production, Employment, GNP deflator, Real wages
Recession (1953-1954)	AO	Real p.c. GNP
	LS	Employment
Tight monetary policy (1957)	AO	Interest rate
Less restrictive monetary policy (1961)	AO	Interest rate
Expansionary monetary and fiscal policies (1968)	IO	Interest rate
Expansionary monetary and fiscal policies (1970)	AO	Interest rate
Volcker disinflation (1980-1981)	IO, TC	Interest rate
Inflation scare (1984)	AO	Interest rate
Fall in oil prices (1986)	LS	Interest rate

Table 10: Results of Efficient Unit Root Tests.

Data series	DF-GLS	MZ_a	MZ_t	k
Real GNP	-0.85	-1.68	-0.82	0
Nominal GNP	-2.01	-7.37	-1.91	0
Real per capita GNP	-0.80	-1.42	-0.76	0
Industrial production	-1.36	-10.87	-1.29	0
Employment	-1.37	-3.78	-1.28	0
Unemployment	-4.39*	-26.90*	-3.67*	0
GNP deflator	-1.44	-10.98	-2.15	5
Consumer prices	-1.89	-8.14	-1.81	0
Nominal wages	-0.28	-0.24	-0.15	0
Real wages	-0.65	-1.51	-0.64	0
Money stock	-2.01	-8.43	-2.01	2
Velocity	-0.58	-1.51	-0.66	6
Interest rate	-0.21	-0.41	-0.19	0
Stock price	-1.00	-3.12	-1.02	5

* Significant at 5% level. Critical values at the 5% level are -2.91 for DF-GLS and MZ_t, and -17.3 for MZ_a. k represents the lag order for efficient unit root tests, and is selected by using the modified Akaike information criteria (MIC) proposed by Ng and Perron (2001).

Appendix

Table 11: Estimated break dates in the Nelson-Plosser data – one break.

Data series	Zivot–Andrews (1992)	Perron (t_α) (1997)	Perron (t_λ) (1997)	Vogelsang (level) (1997)	Vogelsang (diff.) (1997)	Hsu–Kuan (2001)
Real GNP	1929	1928	1928	1929	1938	1940
Nominal GNP	1929	1928	1928	1929	1932	1930
Real p.c. GNP	1929	1928	1928	1938	1921	1940
Ind production	1929	1928	1928	1929	1952	1929
Employment	1929	1928	1928	1929	1906	1929
Unemployment	—	—	—	1929	1933	—
GNP deflator	1929	1928	1919	1920	1940	1930
Consumer prices	1873	1939	1919	1872	1879	1901
Nominal wages	1929	1929	1919	1929	1920	1930
Real wages	1940	1939	1939	1940	1938	1940
Money stock	1929	1927	1928	1928	1920	1930
Velocity	1949	1946	1880	1947	1949	1930
Interest rate	1932	1963	1920	1962	1967	1935
Stock price	1936	1928	1936	1936	1947	1939

Zivot and Andrews (1992) and Perron (1997) proposed unit root tests with one structural break whereas Volgelsang (1997) and Hsu and Kuan (2001) suggested tests for detecting breaks. Perron (t_α) and (t_λ) denote two different inf-t statistics of Perron (1997). Vogelsang (level) and (diff.) denote the level and first-difference statistics of Vogelsang (1997), respectively.

Table 12: Estimated break dates in the Nelson-Plosser data – two breaks.

Data series	Lumsdaine Papell (1997)	Lee Strazicich (2003)	Papell Prodan (2007)
Real GNP	1928	1920	1929
	1937	1941	1939
Nominal GNP	1919	1920	1929
	1928	1948	1949
Real p.c. GNP	1928	1920	1929
	1939	1941	1939
Ind production	1917	1920	1869
	1928	1930	1929
Employment	1928	1920	1908
	1955	1945	1929
Unemployment	1928	1926	—
	1941	1942	—
GNP deflator	1916	1919	1929
	1920	1922	1945
Consumer prices	1914	1916	1882
	1944	1941	1940
Nominal wages	1914	1921	1908
	1929	1942	1929
Real wages	1921	1922	1909
	1940	1939	1940
Money stock	1929	1927	1915
	1958	1931	1930
Velocity	1883	1893	1884
	1953	1947	1949
Interest rate	1931	1949	1932
	1957	1958	1965
Stock price	1925	1925	1886
	1938	1941	1953

Lumsdaine and Papell (1997), Lee and Strazicich (2003) and Papell and Prodan (2007) proposed unit root tests with two structural breaks. As suggested by Perron (1989) and Zivot and Andrews (1992), among others, the estimated break dates are only reported for model A – that allows for changes in the intercept of the trend function – in all series except for the real wages and the stock price, in which cases model C – that allows for changes in the intercept and the slope of the trend function – is assumed.